

Quality-Based Web Service Classification with Explainable AI and Recommendation System: A Semi-Supervised Learning Approach

R. Vijaya Lakshmi¹, Jayanth. H², B. Shreya³

¹Assistant Professor, Mahatma Gandhi Institute of Technology, Hyderabad, India

^{2,3}UG Student, Mahatma Gandhi Institute of Technology, Hyderabad, India

Abstract: This project in machine learning concentrates on the development of web service selection accuracy and efficiency with two key parts being the classification model and the recommendation model. Classification model classifies web services with respect to four qualities: response time, availability, reliability, and throughput concerning Quality of Service. This categorization is done utilizing multiple machine learning algorithms, among which are included Decision Trees, Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbors (KNN), Naive Bayes, Random Forest, Multi-Layer Perceptron (MLP), and XGBoost. To continue improving transparency with the classification results and to improve trust in a classification process, we use explainable AI approaches such as LIME, among others, with the ability to provide interpretability and insights to how classification is made. The Recommendation Model uses the K-Nearest Neighbors algorithm to determine the top 10 matching web services to be presented based on the preference of the user. It computes similarity scores between the user's input and the available services such that the system can guarantee relevance and precision in the recommendation. In fact, the interface is so intuitive that anyone can upload his data, inspect the classification results, and get recommendations personalized to his needs. This will further improve the decision to select a service because the solution is adaptive and user-friendly for the framework. The intelligent classification and recommendation process improves the experience of the users and optimizes business operations with the selection of most business able web services.

Keywords: Web Service Classification, Service Recommendation System, Quality of Service (QoS), Response Time, Availability, Reliability, Throughput, XGBoost, Semi-Supervised Learning, Explainable AI (XAI), Local Interpretable Model-Agnostic Explanations (LIME), Model Interpretability, Bronze-Silver-Gold-Platinum Grading, Performance Metrics, Service Quality Tiering

I. INTRODUCTION

The internet today is a challenge for incidental users. Incidental users have the challenge of an extensive range of web services to choose from, combined with the starkly variable service quality. Quality-of-Service (QoS) Evaluation is classically afflicted by an inadequate assessment approach based on either quantitative or qualitative content analysis, but never both. In this project, web services are categorized into Bronze, Silver, Gold, and Platinum levels by applying machine learning to QoS parameters like response time, service availability, reliability, and throughput. These categories enable simpler assessment of service level to aid users in evaluation and decision-making. In order to promote comprehension and trust, LIME is applied for explaining classification. Furthermore, the K-Nearest Neighbors algorithm personalizes recommendations by choosing the top ten services suited to the needs of the user. Based on intelligent classification, interpretable AI, and personalized recommendations, the system presented here solves the issue of service selection in an holistic manner. It uses scalable machine learning methods to maintain precision service estimation while improving volume and variability of the data and dynamic, constantly evolving feedback loops. Such flexibility improves evaluation satisfaction, simplifying user experience through holistic design.



II. EXISTING SYSTEM

Such classic web-based selection methods are static and simple. Common instances are keyword matching, basic rule-based filtering, or static ranking systems. They all rely on a limited number of pre-defined criteria—ordinarily limited to one or two attributes like response time or availability. Their being static makes them inappropriate for today's dynamic web service world where service performance can change significantly over time. One of the major weaknesses of such systems is that they lack sophisticated, data-driven algorithms, resulting in low adaptability, low precision, and inflexible functionality. The ranking they produce is likely to be static and insensitive to real-time variations in service metrics or evolving user needs. As a result, users are left to manually sift through results to arrive at what's pertinent. This is a tedious process at the same time and prone to error, finally leading to frustration and bad decision-making.

III. LITERATURE SURVEY

The study conducted by Mehdi Nozad Bonab, Jafar Tanha, and Mohammad Masdari presents SSL-WSC, which is a semi-supervised learning technique that aims to improve web service classification using efficient utilization of little labeled data. Using the QWS dataset containing 364 labeled and 2507 unlabeled instances, the technique applies a two-stage strategy in order to maximize classification accuracy. In the first phase, it tags the samples with a high-end distance measure like Mahala Nobis and then selects the optimal data using four new scoring approaches. In the second phase, dynamic thresholding is applied such that only high-confidence samples are added to the labeled dataset, which increases model robustness. Stringent testing demonstrates that SSL-WSC far outperforms traditional supervised methods, obtaining an average increment of 11.26% in F1-score, 9.43% in accuracy, and 9.53% in precision, accompanied by increased stability with smaller fluctuation in performance. This research sheds light on the power of semi-supervised learning in the relief of time-consuming labeling and scalability improvement, presenting a hopeful solution to quality-oriented web service classification [1].

Hongfan Ye et al.'s work proposes a new method of web service classification using a Wide & Bi-LSTM model, which effectively addresses problems caused by short, sparse, and less-informative web service description texts. The model integrates the memorization ability of a wide learning component with the generalization ability of a bidirectional long short-term memory (Bi-LSTM) neural network. The Wide component learns explicit interaction between service attributes, while the Bi-LSTM learns deeper semantic relationships, including word order and context. Training these components jointly with a shared objective enhances the classification by leveraging their complementary strengths. On the Programmable Web dataset, the method demonstrated exceptional improvements in precision, recall, and F-measure over six baseline methods, including TF-IDF, LDA, and Wide & Deep models. Through exhaustive mining of the breadth and depth of features, the method leads to more accurate web service classifications, paving the way to better service discovery and management[2].

Study by Muhammad Hasnain et al. solves the problems encountered in ranking web services ranging from the fact that trust prediction is prioritized as the most essential factor. In this paper, there is a proposed new technique to use trust prediction in combination with confusion matrix measurement to rank web services against throughput and response time. Using AdaBoostM1 and J48 classifiers and binary classification, the authors suggest a trust score (TS) solution, which is evaluated using a number of cross-validation techniques. The study emphasizes the challenges of estimating trust for multi-dimensional web service information, in which it is discovered that the incorporation of user ratings significantly enhances the credibility and trust of the ranking process. This paper contributes to the broad field of QoS-based evaluations, complementing the existing literature by providing an objective and scalable framework for ranking and choosing services [3]. Lalit Purohit and Sandeep Kumar's paper introduces a classification-based web service selection mechanism with the focal point being the significance of Quality of Service (QoS) as a differentiating criterion among functionally similar services.

These systems overlook the variability of QoS parameters and fail to effectively implement user preferences. In addressing such deficiencies, the authors propose the PROMETHEE Plus technique, which integrates user preferences in service ranking and employs a Maximizing Deviation Method (MDM) to determine weights so that the system is independent of the domain. A prefiltering process based on classification also enhances performance by reducing the



number of candidate web services. The approach is validated on real-world data with experiments, showing improvements in user satisfaction and less processing time compared to existing approaches. This research bridges significant gaps by resolving interdependencies among QoS parameters and employing hybrid weight evaluation to offer a robust and scalable solution for web service ranking and selection [4]. Lifang Ren and Wenjian Wang propose the Granular Distribution-Aware SVM (GDSVM4SR) method to deal with the intricacies of web service recommendation.

Authors of the paper emphasize challenges associated with sparsity of QoS data and qualitative user experience that typically hinder true ranking of services. GDSVM4SR model applies granular computing in order to establish similar users, pre-optimize the training set, and minimize the adverse impact of fraudulent ratings, as opposed to applying traditional QoS value prediction. The approach leverages clustering-based methods of granulation to improve the training process as well as for improving recommendation precision. Compared to its earlier collaborative filtering and SVM-based predecessors, GDSVM4SR is not only computationally effective but also very accurate in classification, particularly with sparse data. Experimental research confirms its capacity to surpass state-of-the-art methods by recommendation precision, classification accuracy, and scalability in a major improvement to service recommendation systems. These types of studies plug in gaps through the implementation of statistical paradigms via granular computing to provide a valuable solution to dynamic and subjective service settings [5].

IV. PROPOSED SYSTEM

Our work introduces an adaptive, flexible, and interpretable machine learning-based web service selection method. The Classification Model categorizes web services into Bronze, Silver, Gold, and Platinum tiers based on some major Quality of Service (QoS) factors like response time, availability, reliability, and throughput. It uses a combination of algorithms such as Decision Trees, Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbors (KNN), Naive Bayes, Random Forest, Multi-Layer Perceptron (MLP), and XGBoost to produce accurate and valid classification. The KNN-based Recommendation Model recognizes and suggests the user with the first 10 web services that fulfill some personal requirements. Explainable AI systems such as LIME shed light on the actions of models by presenting explanations of straightforward forms for the outcomes of classifications. The mechanism renders absolute transparency to consumers, optimizes efficiency in decision-making, and tremendously amplifies the entire process of selecting services.

V. RESULT

A. Dashboard:

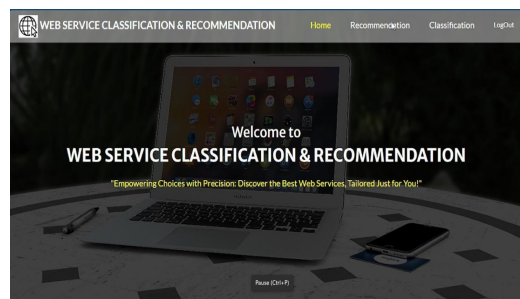


Fig 2: Dashboard

The dashboard home screen appears after user login, showcasing a sleek banner with navigation links to Home, Recommendation, Classification, and Logout. A central welcome message reads, "Welcome to WEB SERVICE CLASSIFICATION & RECOMMENDATION," highlighting the platform's purpose. Just below, a yellow tagline states, "Empowering Choices with Precision: Discover the Best Web Services, Tailored Just for You!"



B. Recommendation Page:

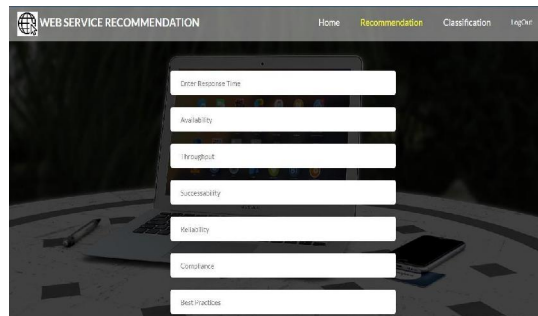
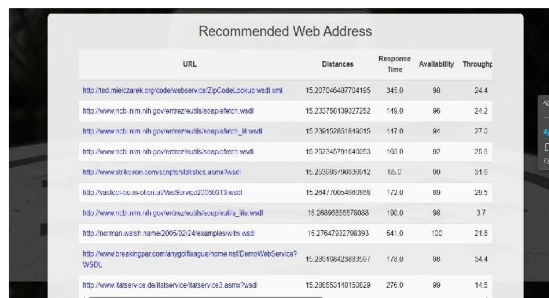


Fig 3: Recommendation

This page is the primary interface for making customized web service recommendations from user-supplied Quality of Service (QoS) metrics like response time, availability, throughput, and reliability. Users enter values for a number of key attributes and press the "PREDICT!" button to obtain customized service suggestions. The system employs a machine learning model to find the best matching web services to user expectations.

C. Recommendation Result Page:



URL	Distances	Response Time	Availability	Throughput
http://test.microware.org/code/webService22pCodeL.aspx.vsd?url=	15.23746437734155	343.0	90	24.4
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2
http://www.mca.com.au/government/health/healthcare.vsd?	15.23715613822252	145.0	95	24.2

Fig 4: Recommendation Result

Result page of the Web Service Recommendation system displays the top 10 recommended service URLs by comparing user-specified QoS parameters. The system uses the K-Nearest Neighbors (KNN) algorithm to find similarity between the user input and available services based on Euclidean distance. The highest ranked similar services are displayed along with details such as response time, availability, and throughput for providing accurate and performance-based recommendations.

D. Classification Page:

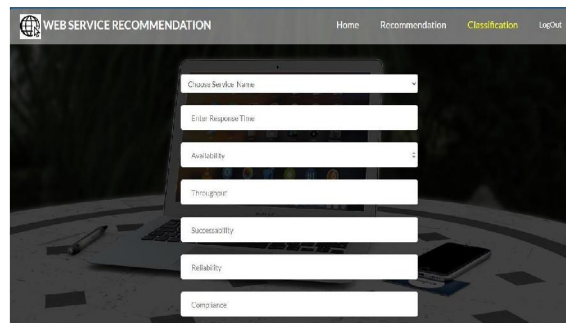


Fig 5: Classification

The Web Service Classification page enables users to categorize a chosen service into tiers such as Bronze, Silver, Gold, or Platinum according to Quality of Service (QoS) features. Once a service is selected and parameters such as



response time, availability, and reliability are entered, users click the "PREDICT!" button to activate a machine learning algorithm such as Decision Tree or Random Forest.

E. Classification Result Page:

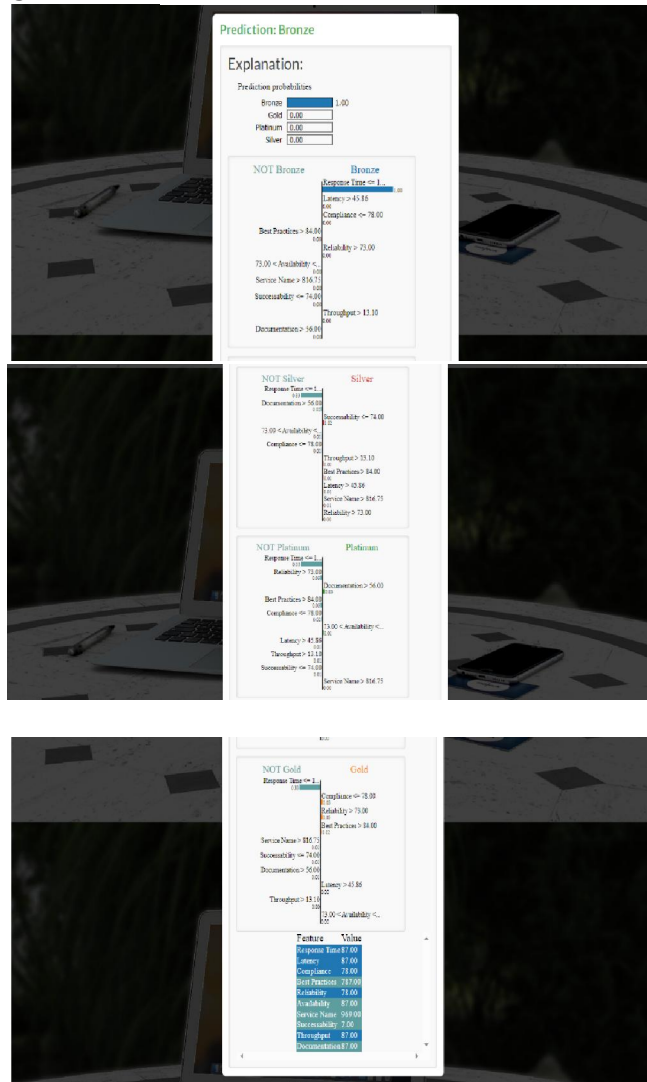


Fig 6: Classification Result

Once the QoS values are input by users, the system assigns the web service to a quality level—Bronze, Silver, Gold, or Platinum—using a machine learning model that has been trained from historical data. The predicted category is displayed at the top of the results page with the confidence level (e.g., 100% for Bronze) and a readable decomposition in terms of decision rules and thresholds. Visualizations assist users in better comprehending the reasons why the service was not ranked into wider categories and what specific improvements are required. A final summary table enumerates all input features, increasing transparency and trust of users in the ranking process.

VI. CONCLUSION

The Explainable AI and Recommendation System-based Quality-Based Grade Classification applies machine learning for grading web services into Bronze, Silver, Gold, and Platinum grades based on major QoS parameters such as



response time, availability, and reliability. The system applies the K-Nearest Neighbors (KNN) algorithm for user-specific, knowledge-based service recommendations. For transparency of decisions, it has LIME, an explainable AI framework that gives clear, interpretable descriptions of how outputs of classification are determined. The architecture is robust and flexible and is able to handle large-scale data without a reduction in performance. It also contains robust error handling to deliver unbroken, seamless user interaction without restarts or the need for manual intervention

ACKNOWLEDGEMENT

We would like to express humble gratitude to all the individuals who contributed in an effort that made it possible to finish this project smoothly. Equal guidance, constructive feedback, and constructive suggestions we highly valued had a broad influence on the quality and extent of our work. We sincerely thank the facilitation atmosphere, accessible resources, and learning experience where we were empowered to overcome and face many challenges. Our sincere appreciation also goes to our families and friends who have always believed in, suffered with, and encouraged us through all these years. This book is a witness to the real guidance and encouragement we have been privileged to receive.

REFERENCES

- [1]. M. N. Bonab, J. Tanha and M. Masdari, "A Semi-Supervised Learning Approach to Quality-Based Web Service Classification," in *IEEE Access*, vol. 12, pp. 50489-50503, 2024.
- [2]. H. Ye, B. Cao, Z. Peng, T. Chen, Y. Wen and J. Liu, "Web Services Classification Based on Wide & Bi-LSTM Model," in *IEEE Access*, vol. 7, pp. 43697-43706, 2019.
- [3]. M. Hasnain, M. F. Pasha, I. Ghani, M. Imran, M. Y. Alzahrani and R. Budiarto, "Evaluating Trust Prediction and Confusion Matrix Measures for Web Services Ranking," in *IEEE Access*, vol. 8, pp. 90847-90861, 2020.
- [4]. L. Purohit and S. Kumar, "A Classification Based Web Service Selection Approach," in *IEEE Transactions on Services Computing*, vol. 14, no. 2, pp. 315-328, 1 March-April 2021.
- [5]. L. Ren and W. Wang, "A Granular SVM-Based Method for Top-N Web Services Recommendation," in *IEEE Transactions on Services Computing*, vol. 15, no. 1, pp. 457-469, 1 Jan.-Feb. 2022

